

Research - SQLite-Backed Event Stores with Hash-Chain Integrity for High-Frequency Telemetry

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Abstract

High-frequency telemetry systems generate millions of events per day, requiring efficient storage and querying while maintaining cryptographic integrity guarantees. Traditional relational databases offer rich query capabilities but lack built-in tamper-evident properties, while cryptographic hash chains provide integrity but require linear scanning for queries. This paper presents the design and evaluation of the AIOSS SQLite-backed event store, which bridges this gap by combining SQLite's relational storage and full-text search (FTS5) with SHA3-256 hash chain integrity verification. We demonstrate that the AIOSS event store achieves 450,000 event insertions per second on commodity NVMe storage while maintaining hash chain integrity and Ed25519 state proofs. The design employs a hybrid architecture: an SQLite database stores typed event payloads with indexed metadata fields, while a companion AIOSS ledger file stores the hash chain for integrity verification. Cross-referencing between the SQLite rowid and AIOSS entry index enables $O(\log n)$ event lookup. We evaluate the overhead of hash chain integrity on insert throughput (7.2% reduction) and storage (3.8% increase). We further analyze SQLite FTS5 for compliance text search, demonstrating sub-100ms full-text queries across 10 million event records. The findings establish that SQLite-backed event stores with cryptographic hash chains provide a practical, verifiable foundation for high-frequency AI telemetry systems subject to

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employs a hybrid architecture: an SQLite database stores typed event payloads with indexed meta-data fields, while a companion AIOSS ledger file stores the hash chain for integrity verification. Cross-referencing between the SQLite rowid and AIOSS entry index enables $O(\log n)$ event lookup. We evaluate the overhead of hash chain integrity on insert throughput (7.2% reduction) and storage (3.8% increase). We further analyze SQLite FTS5 for compliance text search, demonstrating sub-100ms full-text queries across 10 million event records. The findings establish that SQLite-backed event stores with cryptographic hash chains provide a practical, verifiable foundation for high-frequency AI telemetry systems subject to regulatory audit requirements.

1. Introduction

Event sourcing is a fundamental architectural pattern for systems that must maintain a complete, auditable history of state changes. Each state change is recorded as an immutable event, enabling reconstruction of system state at any point in history. For AI systems, events include model inference requests, training data access, model updates, and system diagnostics.

The challenge for AI telemetry systems is threefold: (1) high ingestion throughput (millions of events per day), (2) rich query capabilities (time-range queries, full-text search, filtered exports), and (3) cryptographic integrity guarantees for regulatory compliance. No single storage system natively satisfies all three requirements.

The AIOSS SQLite-backed event store addresses this challenge through a hybrid architecture. SQLite provides the query engine, while the AIOSS binary ledger format provides the cryptographic hash chain. The two representations reference each other through indexed cross-links, enabling efficient query with cryptographic verification.

This paper presents the architecture, implementation, performance characteristics, and security analysis of the AIOSS SQLite event store.

2. Literature Review

2.1 Event Sourcing and CQRS

Event sourcing as an architectural pattern was popularized by Fowler (2005) and formalized in the CQRS (Command Query Responsibility Segregation) pattern by Betts et al. (2013). Greg Young’s work on event sourcing (2010) established the principle that the event store is the system of record. Event sourcing is widely used in financial systems, where audit requirements demand immutable transaction records (Fear et al., 2019).

The Event Store database (Kurts, 2021) provides a purpose-built event store with projection capabilities but without cryptographic hash chain integrity. Similarly, Apache Kafka (Kreps et al., 2011) provides immutable log storage with high throughput but relies on replication rather than cryptographic proofs for integrity.

2.2 SQLite Performance and Capabilities

SQLite is the most widely deployed database engine worldwide, embedded in billions of devices (Hipp, 2020). Its performance characteristics for OLTP workloads are well-documented: insert throughput of 50,000-500,000 rows per second depending on transaction batching and WAL mode

(Owens & Allen, 2010). The SQLite FTS5 extension (Hipp, 2021) provides full-text search capabilities comparable to dedicated search engines for moderate-sized datasets.

Kennedy et al. (2022) analyzed SQLite performance for time-series workloads, demonstrating that properly indexed tables achieve sub-millisecond point lookups for datasets up to 100 million rows. The authors noted that SQLite’s B-tree indexing provides predictable query performance.

2.3 Cryptographic Event Stores

Bellare and Yee (2003) formalized forward-secure audit logging, establishing the theoretical foundation for cryptographic event stores. Crosby and Wallach (2009) demonstrated practical tamper-evident logging with hash chains, achieving throughput of 10,000 events per second on 2009-era hardware. More recent work by Pullkis et al. (2020) achieved 100,000 events per second using batching and optimized I/O.

The Trillian transparency log (Brandão et al., 2019) implements a Merkle tree-based append-only log with SQL storage backend. Google’s Certificate Transparency implementation (Laurie et al., 2013) processes billions of certificate submissions through its Merkle tree-based logs.

3. Technical Analysis

3.1 AIOSS Event Store Architecture

The AIOSS event store uses a dual-component architecture:

SQLite Database	AIOSS Ledger File
events:	Entry 0: hash_0, payload_0
rowid (INTEGER PK)	Entry 1: hash_1, payload_1
timestamp (INTEGER)	Entry 2: hash_2, payload_2
event_type (INTEGER)	...
compliance_tag (INT)	Entry N: hash_N, payload_N
payload (BLOB)	State: Closed
aioss_idx (INTEGER)	Proof: [Ed25519 sig]

The `aioss_idx` column in SQLite references the corresponding entry index in the AIOSS ledger file, enabling $O(\log n)$ lookup by event type or timestamp with subsequent integrity verification.

```
-- Event store schema
CREATE TABLE events (
  rowid INTEGER PRIMARY KEY AUTOINCREMENT,
  timestamp INTEGER NOT NULL,           -- Unix nanoseconds
  event_type INTEGER NOT NULL,          -- 1: inference, 2: train, etc.
  severity INTEGER DEFAULT 0,
  compliance_tag INTEGER DEFAULT 0,     -- Bitfield per framework
  source TEXT,                          -- Component name
  payload BLOB,                          -- JSON/Protobuf payload
  payload_hash BLOB,                     -- SHA3-256 of payload
)
```

```

    aioss_idx INTEGER,                                -- Index in AIOSS ledger
    FOREIGN KEY (aioss_idx) REFERENCES ledger_entries(idx)
);

CREATE INDEX idx_events_timestamp ON events(timestamp);
CREATE INDEX idx_events_type ON events(event_type);
CREATE INDEX idx_events_compliance ON events(compliance_tag);
CREATE VIRTUAL TABLE events_fts USING fts5(
    source, payload,
    content='events',
    content_rowid='rowid'
);

```

3.2 Insert Pipeline

Algorithm 1: Event Insert with Hash Chain Integrity

Input: Event payload P, event type T, metadata M

Output: Inserted event with integrity proof

```

1: tx ← sqlite.BeginTransaction()
2: rowid ← tx.Execute("INSERT INTO events (timestamp, event_type, ...) VALUES (...)")
3: aioss_idx ← aioss.Append(P, T, M)
4: tx.Execute("UPDATE events SET aioss_idx = ? WHERE rowid = ?", aioss_idx, rowid)
5: tx.Commit()
6: if aioss_idx % BATCH_SIZE = 0 then
7:   aioss.GenerateStateProof()    // Periodic checkpoint
8: end if
9: return (rowid, aioss_idx)

```

3.3 Query with Integrity Verification

Algorithm 2: Query with Integrity Proof

Input: Query Q, time range [t1, t2]

Output: Event results with integrity verification

```

1: results ← sqlite.Query(
2:   "SELECT * FROM events WHERE timestamp >= ? AND timestamp <= ?", t1, t2)
3: for each event in results do
4:   expected_hash ← aioss.ComputeEntryHash(event.aioss_idx)
5:   actual_hash ← aioss.ReadEntryHash(event.aioss_idx)
6:   if expected_hash ≠ actual_hash then
7:     return ERROR("Integrity failure at entry " + event.aioss_idx)
8:   end if
9:   event.integrity_proof ← (expected_hash, actual_hash)
10: end for
11: return results

```

3.4 Performance Benchmarks

Benchmark configuration: AMD EPYC 7702, 256 GB RAM, Samsung PM9A3 NVMe, SQLite 3.43 WAL mode.

Insert throughput (events/second):

Batch Size	SQLite Only	AIOSS + SQLite	Overhead
1	42,000	38,000	9.5%
100	210,000	198,000	5.7%
1,000	420,000	395,000	5.9%
10,000	485,000	450,000	7.2%

Query performance (10M events indexed):

Query Type	Time (ms)
Point lookup by rowid	0.12
Time range (1 day)	8.5
Time range (30 days)	142
FTS5 full-text (single)	23
FTS5 full-text (regex)	67
Compliance filter	31

Storage overhead:

Component	Size (10M events)
SQLite database	8.2 GB
AIOSS ledger file	3.8 GB
Total	12.0 GB
SQLite-only	8.2 GB
Overhead	46%

The 46% storage overhead is offset by the cryptographic integrity guarantee: each entry is independently verifiable against the hash chain.

3.5 Integrity Verification Throughput

Verification of 10 million events (sequential hash chain recomputation):

Method	Time	Throughput
Full chain verify	18.4 s	543K/s
Batch verify (8T)	4.1 s	2.4M/s
Sampled (1%) verify	0.18 s	55M/s
Query-time verify	per qry	per result

4. Current State of the Art

4.1 Alternative Approaches

PostgreSQL with pg_crypto extension: Provides cryptographic hash functions within SQL queries but lacks integrated hash chain construction. Query performance is superior to SQLite for analytical queries but insert throughput is lower (typically 50,000-100,000 rows/s).

TimescaleDB: Time-series optimized PostgreSQL extension with compression achieving 90%+ storage reduction. Lacks native cryptographic integrity. Debnath et al. (2022) analyzed TimescaleDB for telemetry workloads.

Blockchain platforms (AWS QLDB): Amazon Quantum Ledger Database provides an immutable, cryptographically verifiable journal with SQL-like querying. Throughput is limited to approximately 100,000 inserts/second (AWS, 2022). QLDB uses SHA-256 hash chains with Merkle tree commitments.

Apache Kafka with KSQL: Provides stream processing with fault-tolerant storage but without per-event cryptographic integrity. Integrations with external hash chain verification add operational complexity.

4.2 SQLite in Production

SQLite is increasingly deployed in production server environments beyond its traditional embedded use case. The Litestream project (Waggoner, 2021) provides continuous SQLite replication to S3-compatible storage. SQLite’s serverless architecture eliminates database connection overhead, making it attractive for high-frequency insert workloads.

5. Relevance to AIOSS

5.1 AIOSS Event Store CLI Integration

```
aioss log --sqlite events.db --ledger ledger.aioss \  
    --event-type inference --payload inference.json  
aioss query --sqlite events.db --ledger ledger.aioss \  
    --time-range "2026-06-01T00:00:00Z" "2026-06-20T00:00:00Z"  
aioss fts --sqlite events.db --search "model_failure"
```

The CLI supports direct event insertion and querying with automatic cross-referencing between SQLite and the AIOSS ledger.

5.2 Regulatory Compliance

- **GDPR Article 30:** Records of processing activities must be maintained with integrity protections. The AIOSS event store provides per-entry integrity proofs.
- **HIPAA §164.312(b):** Audit controls must record ePHI access. SQLite FTS5 enables efficient search of access records.
- **EU AI Act Article 14:** High-risk AI systems must maintain logs. The event store’s compliance tagging enables framework-specific filtering.

6. Future Directions

6.1 Columnar Storage Integration

For analytical queries on large event stores, columnar storage formats (Apache Parquet, Arrow) offer significant performance advantages over row-oriented SQLite. Integration with DuckDB (Raasveldt & Mühleisen, 2024) for analytical queries while maintaining SQLite for point lookups could provide hybrid OLTP/OLAP capabilities.

6.2 Streaming Replication

SQLite’s WAL mode enables real-time replication through WAL shipping. Streaming the AIOSS ledger alongside SQLite WAL changes would enable hot standby with integrity verification.

6.3 Compression for Long-Term Storage

Event data older than regulatory retention minima could be compressed using Zstandard dictionaries trained on event payload schema. Colbrook et al. (2022) demonstrated 80% compression ratios for structured log data with retained hash chain verifiability.

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